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AUTHOR Wolfle, Lee M.; Ethington, Corinna A.
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ABSTRACT

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A PROGRAM FOR STANDARD ERRORS OF INDIRECT EFFECTS IN RECURSIVE CAUSAL MODELS

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Lee M. Wolfle

and

Corinna A. Ethington

Virginia Polytechnic Institute and State University

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ABSTRACT

In his early exposition of path analysis, Duncan (1966, p. 7) noted that the method "provides a calculus for indirect effects." Despite the interest in indirect causal effects, most users treat them as if they are population parameters and do not test whether they are statistically significant. Sobel (1982) has recently derived the asymptotic distribution of indirect effects. His algorithm involves calculating partial derivatives of indirect effects with respect to structural parameters, which if done by hand is tedious and subject to computational errors. This paper describes a new FORTRAN computer program that provides the causal modeler with standard errors of indirect effects for recursive causal models. The only input data required is a matrix of structural parameter estimates along with their variances and covariances.

A PROGRAM FOR STANDARD ERRORS OF INDIRECT EFFECTS IN RECURSIVE CAUSAL MODELS

In his early exposition of path analysis, Duncan (1966, p. 7) noted that the method "provides a calculus for indirect effects." In recursive causal models, direct causal effects are estimated by the magnitude of regression coefficients. Indirect causal effects are estimated by the magnitude of the sum of the products of causal effects through intervening variables. Early expositions of path analysis failed to distinguish between indirect causal effects and noncausal components, but this misconception was soon corrected by Duncan (1971) and independently by Finney (1972). Nonetheless, calculation of indirect effects remained a tedious procedure, whether one used the basic algebraic theorem of path analysis (Duncan, 1966, p. 5) or the path-tracing technique (Duncan, 1966, p. 6).

Alwin and Hauser (1975) helped to alleviate this tedium by describing a general method for decomposing causal components. Their method of calculating indirect effects involved successive computation of reduced-form equations, and taking differences between reduced-form and final-form coefficients. Alwin and Hauser's (1975) strategy, however, is applicable only to just-identified recursive models. Subsequently, Fox (1980) introduced a more efficient and general technique for calculating indirect effects. His strategy for calculating total indirect effects involved raising a matrix of direct effects to successive powers and summing the results. Joreskog and Sorbom (1983,

p. III.39) have since provided a more general procedure that holds for models with or without latent variables, for recursive or nonrecursive models, and for just-identified or overidentified models.

Despite the enormous interest in estimating indirect causal effects, their probability distribution was for a long time unknown. Most users of causal modeling techniques treated estimates of indirect effects as if they were population parameters and did not test whether they were statistically significant. Not atypical were such statements as, "Although father's occupation exerts a small direct effect on son's occupation, it has a sizable indirect effect." With large sample sizes, of course, one could assume a "sizable indirect effect" was also statistically significant, yet in the absence of its statistical distribution, one could never be sure. When either the magnitudes of indirect effects or sample sizes were small, one remained in doubt as to the statistical significance of indirect effects.

Bobko and Rieck (1980) and Sobel (1982) have independently corrected this uncertainty by deriving the asymptotic distribution of indirect effects for large sample sizes. Of the two, Sobel's (1982) is more elegant and computationally straightforward. By assuming estimates were obtained by a maximum-likelihood (or an asymptotically equivalent) procedure from a large sample, Sobel (1982) first determined the asymptotic distribution of the coefficient vector for recursive causal models, and subsequently for nonrecursive models. He then utilized the multivariate-delta method for evaluating the asymptotic distribution of indirect effects, which are simply nonlinear functions of structural

coefficients. In his own words, Sobel's (1982, p. 293) method "provides a simple, general, and elegant means for evaluating the asymptotic distribution of functions of multivariate normally distributed random variables."

Sobel (1982) illustrated the ease with which the standard errors of indirect effects could be calculated with a model taken from Duncan, Featherman, and Duncan (1972). Although any good matrix algebra program could assist in multiplying matrices, Sobel's illustration involved calculating by hand partial derivatives of indirect effects with respect to structural parameter estimates. Calculating partial derivatives by hand, however, is tedious and error prone, which may serve to limit the useful application of Sobel's technique.

The main purpose of this paper is to introduce a FORTRAN computer program that calculates standard errors of indirect effects for recursive causal models. (Although Sobel's [1982] method is not restricted to the recursive case, we have imposed this limitation on the program because most causal models employed in the social sciences are recursive, and because an algorithm for calculating standard errors of indirect effects in nonrecursive models is rather more programmatically complicated.) By introducing an algorithm for calculating the partial derivatives of indirect effects with respect to structural parameter estimtes, we have been able to eliminate all hand calculations for estimating the standard errors of indirect effects. The only input data required is a matrix of structural parameter estimates along with their variances and covariances. We will first introduce the algorithm used to

estimate the standard errors of indirect effects, and will then present several examples from the extant literature. We assume the reader is already familiar with the topic of structural equation models and the literature on indirect causal effects.

Estimating Standard Errors of Indirect Effects

The computer program we have called SEINE requires the input of a title card, the specification of the number of variables in the model and the number of endogenous variables, labels for the variables, an input format statement for reading the structural parameter estimates, the structural parameter estimates, an input format statement for reading the variance-covariance matrices among the structural coefficients for the several equations in the model, and the variance-covariance matrices. With these data, the calculation of the standard errors of indirect effects is accomplished in the following steps:

(1) The program first calculates the indirect effects using Fox's (1980) algorithm of raising the matrix of structural parameter estimates to successive powers (until obtaining a zero matrix) and summing the results. Consequently, the present program calculates total indirect effects and their standard errors, and does not consider the individual components of such effects.

(2) The program next calculates the partial derivative of each indirect effect with respect to each direct effect. These derivatives are calculated by taking advantage of the fact that in recursive causal models the partial derivative of an indirect effect with respect to a structural parameter can be calculated

by setting that structural parameter to unity if it is a component of the indirect effect. The partial derivative after this substitution is then the sum of the products of the components of that indirect effect. If the structural parameter is not a component of the indirect effect, the partial derivative is zero.

(3) The estimated asymptotic variance-covariance matrix of indirect effects is then estimated by premultiplying the variance-covariance matrix among the structural parameters by the calculated matrix of partial derivatives, and postmultiplying by the transpose of the matrix of partial derivatives.

(4) The standard errors of indirect effects are then obtained by taking the square roots of the diagonal elements in the estimated variance-covariance matrix of indirect effects.

(5) The program then reprints the control cards used to set up the calculations, prints the variance-covariance matrix among structural parameters if desired, the matrix of partial derivatives if desired, the matrix of direct effects, the matrix of standard errors of the direct effects and their t-values if desired, the matrix of indirect effects, the matrix of standard errors of indirect effects, and the ratio of the indirect effects to their standard errors.

The program is restricted to calculating standard errors of indirect effects for recursive models of fifteen variables or less, but it is not restricted to just-identified recursive models and can estimate over-

identified recursive models and block-recursive models as well (see Wolfle, 1980). The user will have to supply structural parameter estimates for the model (including zero coefficients in the case of over-identified or block-recursive models). The user will also have to input the variance-covariance matrix of structural coefficients for each equation in the model; these coefficients are obtainable from most regression programs (e.g., PROC REG in SAS, SPSS-X, or LISREL). With these coefficients in hand, setting up the input to the program is quite simple.

As Sobel (1982, p. 308) pointed out, one caveat is in order. The standard errors obtained in this program are valid for large samples and may not be appropriate for small samples. Boomsma (1982) has found that sample sizes should exceed 400 in order to obtain reliable standard errors of maximum-likelihood estimates; in the absence of multivariate normality among the variables, samples sizes should be even larger.

Illustrative Applications

To illustrate the ease by which users can obtain standard errors of indirect effects, the example used by Sobel (1982), also used by Alwin and Hauser (1975), and taken originally from Duncan, Featherman, and Duncan (1972, pp. 37-45) will be estimated. The model of socioeconomic achievement considers one's educaticnal attainment to be caused by three exogenous measures of socioeconomic background -- father's occupational status, father's educational attainment, and the number of siblings. Son's occupational status is considered dependent upon educational attainment and the three exogenous variables. The son's income is seen to be caused by occupational status, educational attainment, and the

three exogenous variables. The data pertain to nonblack men with nonfarm backgrounds in the experienced civilian labor force at ages 35-44 in March, 1962.

Sobel (1982) has already demonstrated that the indirect effects in this model are all statistically significant at the .01 level of probability. We make no claim here to have added anything original to the analysis of the Duncan, Featherman, and Duncan (1972) model; our purpose is simply to show the results produced by the SEINE program, and the ease with which they were obtained. Table 1 gives these results. The top panel presents the structural coefficients for the model. The next panel gives the indirect effects in structural form, and the bottom panel presents the asymptotic standard errors for the indirect effects. All of the indirect effects are large enough in comparison to their standard errors to conclude that the indirect effects are statistically significant. By way of illustration, note that the direct effect of father's education on son's occupational status is .05, which is not statistically significant. The indirect effect, however, of father's education on son's occupation is .75, which is over ten times as large as its standard error. In other words, the influence of father's education on son's occupational status occurs predominantly (and significantly) through the son's own educational attainment and its subsequent influence on his own occupational achievements.

Insert Table 1 About Here

To demonstrate the ease with which the results shown in Table 1 were obtained, the control cards used as input to SEINE are reproduced in Table 2. The first input line is a title card. The second line indicates that there are 6 variables in the model, 3 of which are endogenous. Labels for the 6 variables are input next in reverse causal order. Thus INCOME is caused by the variables listed below it, but does not cause any of them in return. Similarly, OCCUP is a cause of INCOME, and is caused by the variables listed below it. Exogenous variable labels can be listed in any order, as long as the user is consistent in ordering labels, structural parameter estimates, and their variances and covariances. The next line is an input format statement used to read the structural parameter estimates, which come next. First, the structural parameter estimates for INCOME are given in the same order as the labels are input. There will be, of course, as many lines of structural parameters as there are endogenous variables. Following the structural parameter estimates is another input format statement for reading the variance-covariance matrix for the structural parameter estimates. These matrices are symmetrical, so only the diagonal and lower diagonal elements need be input. These matrices are input in the same order as were the structural equations. With these controls and data, the calculation of asymptotic standard errors for indirect effects proceeds, and yields the results shown in Table 1.

Insert Table 2 About Here

To further illustrate the advantages to be obtained from the easy calculation of standard errors of indirect effects, we have applied our program to a number of modeis in the extant literature. Three examples were selected for discussion based on what was for us their illustrative interest.

Our first new example is taken from Duncan (1966). Based on an earlier analysis by Duncan and Hodge (1963), Duncan (1966) analyzed the longitudinal process of occupational careers as influenced by socioeconomic origins. He lacked a real cohort of U.S. men whose experiences had been traced over time, but was able to estimate his model with a synthetic cohort using data from Duncan and Hodge (1963). His analysis of these data suggested that the early stages of a man's career depend upon socioeconomic background factors (father's occupational status and repondent's education). After the age of 35-44, however, the direct effects of these background variables become negligible, although respondent's education maintains at all ages a degree of importance greater than that of father's occupational status. Compensating for the declining influence of social background is an increasing stabilization of occupational standing after age 35-44.

Thus, U.S. men from advantaged families tend to enter occupations of higher status, and because occupations tend to stabilize over the course of a lifetime, tend to maintain their higher occupational standing. Still at issue is whether the indirect effects of socioeconomic origins are statistically significant causes of occupational status at older ages. That is, by the time a man has reached age 55-64, do his status origins

continue to have an influence on his status through his intervening occupational achievements, or like the direct effects of background, do they become negligible and statistically insignificant over time? To answer these questions, the statistical significance of the indirect structural effects implied by Duncan's (1966, Fig. 4) model were determined. Using an estimated sample size of 1105, which was the number of respondents in Duncan and Hodge's (1963) analysis, the indirect effects, and the standard errors of the indirect effects were calculated using SEINE. To further illustrate how data are input, the SEINE control cards for this example are shown in Table 3. The output is shown in Table 4. The coefficients in Table 4 clearly show that all of the indirect effects of education and father's occupational status on occupational prestige are statistically significant at every age. In summary, social origins most strongly affect a man's occupational status early in life, but continue to manifest their influence throughout life via his intervening achieved statuses.

Insert Tables 3 and 4 About Here

Our second example points out the hazards involved in drawing substantive conclusions from indirect effects without first determining whether they are statistically significant. Biniaminov and Glasman (1983) were primarily interested in the effects of a school's fiscal resources and the level of disadvantaged students on student achievement. Using a sample of Israeli secondary schools, Biniaminov and Glasman developed a

fully-recursive causal model in which the causal order flowed from the level of disadvantaged students to the level of fiscal resources, hence to teachers' teaching experience in the same school, and finally to the number of government certified graduates.

Biniaminov and Glasman's (1983) analysis of the estimated coefficients in their model led them to conclude, "The level of fiscal resources was found to be a negative and direct predictor, but also a positive and indirect predictor through teachers' length of tenure. The level of disadvantaged students was found to be a positive predictor through fiscal resources and teachers' tenure [together], and a negative predictor through each of the inputs separately." To determine if these conclusions were warranted, we reestimated the coefficients in Biniaminov and Glasman's model. The SEINE estimates for this model are shown in Table 5, and indicate that none of the indirect effects in the model are statistically significant. In sum, Biniaminov and Glasman drew their conclusions about the indirect effects from estimated structural effects that were not statistically significant. Conventional statistical wisdom should have dictated the conclusion that the effects in the population were indistinguishable from zero within sampling error limits. Contrary to Biniaminov and Glasman's claim that the level of disadvantaged students influence student achievement, had they compared their estimated indirect-effect coefficients to their standard errors, they would have had to conclude that these effects did not exist in the population.

Insert Table 5 About Here

The example from Biniaminov and Glasman (1983) pointed out the dangers of drawing substantive conclusions from indirect-effect coefficients without first determining whether they were statistically significant. The next example demonstrates the opposite case, for the authors (Peng and Jaffe, 1979) were seemingly overcautious in drawing conclusions about indirect causal effects in the absence of a determination of their statistical significance. Had the authors been convinced of the statistical significance of their results, they may have been able to make more definitive declarations of the causal effects of variables through intermediary processes.

Peng and Jaffe (1979) were interested in the process by which women decide to enter male-dominated fields of study in higher education. Using data from the National Longitudinal Study of the High School Class of 1972 (Riccobono, et al., 1981), the model analyzed by Peng and Jaffe (1979) included sixteen variables arranged into six causal blocks, which included family background, high school experience, academic ability, life goals, educational plans, and entry into a male-dominated field. Using correlations from Peng and Jaffe (1979, Table 1) with means and standard deviations kindly supplied by Peng, the model analyzed by Peng and Jaffe was reestimated with one minor change. As it currently exists, SEINE can only analyze causal models with fifteen or fewer variables. In order to accomodate Peng and Jaffe's model, we dropped from the analysis one of the four tests of academic ability. Heyns and Hilton (1982) have discussed the tests used in both the National Longitudinal Studies of 1972 and 1980. They note that the

letter-group test has in general not been found to be a very useful test of ability, and was therefore dropped from the battery of tests administered in 1980. Accordingly, this variable was dropped from our reanalysis of Peng and Jaffe's model.

The first issue addressed by Peng and Jaffe (1979, p. 291) in the analysis of their results was whether or not family background had an impact on a woman's decision to enter a male-dominated field. They found that the direct effects, which are shown in Table 6, were not statistically significant, but went on to note that parents' educations were positively related to enrollment in high school academic programs, higher test scores, and higher educational plans, which in turn positively influenced women's entry into male-dominated fields. As we read these comments, they seemed to imply the possibility that the indirect effects of family background were significant. Our computation of the indirect effects and their standard errors, however, shown in Table 7, indicates that these effects were not statistically significant. Apparently family background plays no role either directly or indirectly in the decision of women to enter male-dominated fields.

Insert Tables 6 and 7 About Here

Not discussed by Peng and Jaffe (1979) was the strange indirect relationship of academic ability to the decision to enter a male-dominated field. The direct effect of math ability, for example, as noted by Peng and Jaffe (1979, p. 291) was positive and significant, indicating that

mathematical skill enhances a woman's entry into a male-dominated field. The indirect effect of math ability, however, is negative and as indicated in Table 7 statistically significant. For women, higher math ability has a relatively strong and negative influence on the work and community scales included in Peng and Jaffe's analysis. These are multi-variable factors, but include such items as being successful in a chosen line of work, having a lot of money, finding steady work, and being a leader in one's community. These variables in turn have a positive influence on the decision to enter a male-dominated field. In combination, it appears that women with higher math ability tend not to value the factors measured by the work and community scales, yet these in turn lead women to enter male-dominated fields of study. Thus, the relationship between math ability and entering a male-dominated field is not nearly as simple as implied by Peng and Jaffe, for it incorporates both positive direct effects and negative indirect effects through intervening life-goal variables.

Summary

The purpose of this paper has been to introduce a new computer program that calculates standard errors of indirect effects in recursive structural equation models. Following the work of Sobel (1982), who derived the asymptotic distribution of indirect effects, we have discovered an algorithm for calculating partial derivatives of indirect-effect coefficients with respect to their direct-effect components. Incorporating this algorithm into a FORTRAN computer program called SEINE, we have made the calculation of standard errors in recursive causal models a relatively easy task.

To illustrate the application of SEINE, we reanalyzed the same model used by Sobel (1982) to illustrate his derivation of the asymptotic confidence limits of indirect effects. We have also shown how previous research has suffered from not being able to assess the statistical significance of indirect effects. Some authors were led to substantively interpret effects that turned out to be statistically indistinguishable from zero. Other authors have failed to take into proper consideration indirect effects that were statistically significant and substantively relevant to the interpretations of effects in their models.

In summary, researchers employing structural equation techniques have for many years been interested in indirect causal effects. While rigorous methods for testing hypothesized direct effects in causal models have been employed to assess their statistical significance, indirect effects were treated as if they were population parameters. Following the statistical development described by Sobel (1982), the program described here now makes available to the causal-model analyst an easily accessible method for calculating standard errors of indirect effects in recursive structural equation models. We believe such coefficients should become a part of the presentation of structural equation results in the same way that reporting standard errors of direct effects has become routine.

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APPENDIX

The methods described in this paper are relatively easy to program. The program requires the input of structural parameter estimates and the variance-covariance matrix of structural estimates for each equation in the model. From these data, the program calculates the indirect effects, calculates a matrix of partial derivatives, and then uses standard matrix operations to generate the standard errors. While the subroutine for calculating partial derivatives is rather involved programmatically, basically all that is required is that each nonzero indirect effect be evaluated as to whether or not each direct effect is involved in the indirect coefficient. We have checked SEINE results against a number of hand-calculated models, and have not found any computational errors in the program. Nonetheless, no warranty is made as to the accuracy and functioning of SEINE. A FORTRAN program that performs the computations described in this paper is available at a small charge for processing and duplication; address inquires to the authors.

Table 1. SEINE Summary of Causal Effects in Duncan, Featherman, and Duncan (1972)

Predetermined Variables	Endogenous Variables		
	Income	Occupation	Education
Matrix of Direct Effects			
Occup.	.070		
Educ.	.200	4.377	
FaOcc.	.011	.135	.038
FaEduc.	.071	.049	.171
Siblings	-.037	-.463	-.228
Matrix of Indirect Effects			
Educ.	.308		
FaOcc.	.029	.168	
FaEduc.	.090	.747	
Siblings	-.148	-.998	
Matrix of Standard Errors of Indirect Effects			
Educ.	.021		
FaOcc.	.002	.012	
FaEduc.	.012	.071	
Siblings	.014	.082	

Table 2. SEINE Control Cards Used to Estimate Duncan, Featherman, and Duncan (1972)

```
STANDARD ERRORS FOR DUNCAN, ET AL. (1972)
  6  3
INCOME
OCCUP
EDUC
FAOCC
FAED
SIBLINGS
(5F10.7)
    .07043    .19979    .01139    .07117   -.03727
   4.37671    .13517    .04901   -.46310
    .03846    .17074   -.22807
(5E10.3)
 2.020E-05
-8.841E-05    .00132
-2.730E-06-2.412E-05 2.025E-05
-9.900E-07-1.558E-04-5.123E-05 7.593E-04
 9.355E-06 1.730E-04 5.960E-06 1.200E-04 9.885E-04
    .01447
-5.564E-04 3.066E-04
   -.00247-7.923E-04    .01171
    .00330 1.115E-04    .00186    .01518
 6.141E-06
-1.910E-05 2.431E-04
 5.132E-06 5.214E-05 3.107E-04
```

Table 3. Seine Control Cards Used to Estimate Duncan (1966, Fig. 4)

```
INDIRECT EFFECTS ANALYSIS FOR DUNCAN (1966, FIG. 4)
  6  4  1  1  1
OCC55-64
OCC45-54
OCC35-44
OCC25-34
EDUC
FAOCC
(5F10.7)
   .799914         0         0  1.067271   .034104
   .721191         0   .928275  -.011157
   .391194  1.689380   .112246
  3.225158   .154981
(5E10.3)
.000278042
-.00084985 .01555538
-.00003156-.00054194.000239680
.000486712
-.00143631 .02571859
-.00008414-.00080999.000405920
.000766239
-.00247124 .04189974
-.00011875-.00128868.000636617
 .04018210
-.00197973.000732136
```

Table 4. SEINE Summary of Causal Effects in Duncan (1966, Fig. 4)

Predetermined Variables	Endogenous Variables			
	Occ 55-64	Occ 45-54	Occ 35-44	Occ 25-34
Matrix of Direct Effects				
Occ 45-54	.800			
Occ 35-44	---	.721		
Occ 25-34	---	---	.391	
Educ.	1.067	.928	1.689	3.225
FaOcc.	.034	-.011	.112	.155
Matrix of Indirect Effects				
Occ 35-44	.577			
Occ 25-34	.226	.282		
Educ.	2.445	2.128	1.262	
FaOcc.	.091	.125	.061	
Matrix of Standard Errors of Indirect Effects				
Occ 35-44	.021			
Occ 25-34	.018	.022		
Educ.	.172	.158	.119	
FaOcc.	.022	.020	.011	

Table 5. SEINE Summary of Causal Effects in Biniaminov and Glasman (1983)

Predetermined Variables	Endogenous Variables		
	Certified Graduates	Teachers' Experience	Fiscal Resources
Matrix of Direct Effects			
Teach. Ex.	4.428		
Fiscal	- 3.245	.116	
Disad.	-39.831	-3.257	16.912
Matrix of Indirect Effects			
Fiscal	.514		
Disad.	-60.609	1.964	
Matrix of Standard Errors of Indirect Effects			
Fiscal	.558		
Disad.	32.990	2.062	

Table 6. Summary of Direct Causal Effects in Peng and Jaffe (1979)
(Standard Errors Shown in Parentheses)

Predetermined Variables	Endogenous Variables										
	MaleDom	EdPlans	FamScale	ComScale	WrkScale	MathTest	ReadTest	VocTest	MathSem	SciSem	HSProg
EdPlans	-.039 (.011)										
FamScale	-.042 (.019)	-.022 (.039)									
ComScale	.018 (.019)	.217 (.037)									
WrkScale	.135 (.024)	.022 (.047)									
MathTest	.003 (.001)	.002 (.003)	.004 (.001)	-.005 (.001)	-.003 (.001)						
ReadTest	.002 (.001)	.004 (.003)	-.002 (.001)	-.001 (.002)	-.003 (.001)						
VocTest	-.001 (.001)	.009 (.002)	-.003 (.001)	-.004 (.001)	-.004 (.001)						
MathSem	.014 (.005)	.045 (.011)	-.001 (.006)	.007 (.006)	.009 (.005)	1.140 (.104)	.519 (.114)	.285 (.121)			
SciSem	.027 (.005)	.018 (.010)	-.012 (.006)	.006 (.006)	.004 (.005)	.440 (.105)	.263 (.115)	.438 (.122)			
HSProg	-.028 (.020)	.282 (.040)	-.005 (.023)	.038 (.024)	-.018 (.019)	6.202 (.381)	5.243 (.418)	5.850 (.444)	1.357 (.081)	1.183 (.080)	
MaOcc	.042 (.027)	.121 (.054)	-.013 (.031)	.062 (.032)	.012 (.026)	-.722 (.554)	.018 (.607)	.235 (.646)	.004 (.126)	.280 (.125)	-.033 (.034)
FaOcc	.028 (.024)	.034 (.047)	-.019 (.027)	-.037 (.028)	.001 (.022)	.880 (.482)	.246 (.528)	.183 (.561)	-.053 (.110)	-.135 (.109)	-.002 (.029)
MaEd	-.005 (.005)	.024 (.010)	-.004 (.006)	-.006 (.006)	-.007 (.005)	.318 (.105)	.394 (.115)	.464 (.122)	-.011 (.024)	-.018 (.024)	.024 (.006)
FaEd	.003 (.004)	.022 (.009)	-.007 (.005)	-.011 (.005)	-.006 (.004)	.247 (.087)	.381 (.096)	.557 (.102)	.025 (.020)	.017 (.020)	.029 (.005)

Table 7. SEINE Summary of Indirect Causal Effects in Peng and Jaffe (1979)
(Standard Errors Shown in Parentheses)

Predetermined Variables	Endogenous Variables									
	MaleDom	EdPlans	FamScale	ComScale	WrkScale	MathTest	ReadTest	VocTest	MathSem	SciSem
FamScale	.001 (.002)									
ComScale	-.008 (.003)									
WrkScale	-.001 (.002)									
MathTest	-.001 (.000)	-.001 (.000)								
ReadTest	-.001 (.000)	-.000 (.000)								
VocTest	-.001 (.000)	-.001 (.000)								
MathSem	.002 (.002)	.007 (.003)	.003 (.002)	-.008 (.002)	-.007 (.001)					
SciSem	.001 (.001)	.006 (.002)	.000 (.001)	-.004 (.001)	-.004 (.001)					
HSProg	.051 (.011)	.178 (.021)	-.008 (.011)	-.061 (.012)	-.056 (.010)	2.068 (.173)	1.017 (.163)	.905 (.172)		
MaOcc	.003 (.007)	.007 (.020)	-.007 (.004)	.004 (.005)	.004 (.005)	-.149 (.319)	-.133 (.225)	-.101 (.239)	-.045 (.046)	-.039 (.040)
FaOcc	-.003 (.006)	-.012 (.017)	.004 (.003)	-.006 (.004)	-.004 (.004)	-.136 (.277)	-.075 (.194)	-.087 (.206)	-.003 (.040)	-.002 (.035)
MaEd	-.002 (.001)	.014 (.004)	-.001 (.001)	-.005 (.001)	-.006 (.001)	.178 (.060)	.140 (.043)	.151 (.046)	.033 (.009)	.028 (.008)
FaEd	-.000 (.001)	.019 (.003)	-.002 (.001)	-.005 (.001)	-.006 (.001)	.280 (.051)	.202 (.037)	.214 (.039)	.040 (.008)	.035 (.007)